Clinical diffusion imaging: Can we still use corrupted images in voxelwise analysis?

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Introduction: Clinical diffusion imaging is very demanding with respect to acquisition time, on the one hand, and obtaining images of sufficient quality to permit its use in various medical treatments, on the other. Multiple artefacts originate either from the subjects such as bulk head motions, cardiac pulsation, respiratory motion, involuntary tics and tremor, or hardware related problems, such as table vibration in diffusion-weighted measurements [1-3]. As a result, artefacts can severely degrade the resulting images and render the post-processing of diffusion analysis difficult or even impossible. We have developed a novel, robust post-processing framework based on the modified least trimmed squares estimator (MLTS) [4]. We have demonstrated that after applying this framework clinical images substantially corrupted by different artefacts can be used in further analysis, for example, in TBSS.

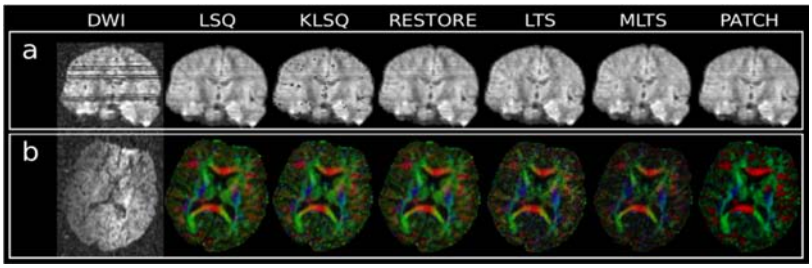

Figure 1. The original and reconstructed diffusion data with each of the 6 algorithms for one subject. a) Coronal projections of the original corrupted and post-processed data. b) One corrupted axial DWI projection (left column) and colour-coded FA maps obtained using the 6 post-processing algorithms (columns from 2 to 7).

Methods: At the heart of the framework is the MLTS algorithm based on the rearranging of the residuals in the non-linear least trimmed squares algorithms. The conventional least trimmed squares (LTS) algorithm [3] is based on truncation of ordered residuals $r_1<r_2<...<r_N$, where N is a number of diffusion gradients. The modified algorithm is rearranging the residuals r_i in the following manner: v_i = abs[r_i-median(r_j)], and operates with newly ordered parameters: $v_1<v_2<...<v_N$. We applied the robust framework to a Tourette patient group where multiple artefacts produced by Tourette-related tics corrupted the measured datasets. Diffusion-weighted images were acquired on 1.5T Sonata Vision MR machine (Siemens Medical Systems, Erlangen, Germany) with an 8-channel phased array head RF coil and a maximum gradient strength of 40 mT/m. The diffusion-weighted data were acquired using the following parameters: 2 mm slice thickness, no inter-slice gap, repetition time TR = 11000 ms, echo time TE = 89 ms, field-of-view FOV = 256 × 208 mm^2, imaging matrix = 128 × 104, number of slices in the transverse orientation = 71. The Tourette patient (11 patients with corrupted datasets and 11 patients without any artefacts) and control group (22 volunteers) selection criteria were described in detail in [5].

Results: In order to demonstrate the advantages of the developed framework we compared it with other approaches: LSQ [6], constrained LSQ (KLSQ) [6], RESTORE [1], PATCH [2], and original LTS [3]. The results are presented in Fig. 1. The original DWI image exhibited many slices corrupted by patient motion (Fig.

1a). Algorithms such as LSQ, KLSQ and RESTORE experience problems with the signal recovering. The PATCH algorithm exhibited acceptable results but produced some additional suspicious slices where signal distortions can visually be detected. The LTS and MLTS approaches restored the signal with better accuracy compared to the other algorithms (Fig. 1b). In Fig. 2 we show the results of the TBSS analysis for a full Tourette patient group with and without distorted datasets in order to emphasize the potential use of images recovered by the robust framework. The regions with substantially ($p<0.005$) decreased FA in Tourette patients have to be compared with the results obtained in [5]. The comparison with Figs. 1 and 2 in Ref. [5] exhibits a good agreement with TBSS results obtained here.

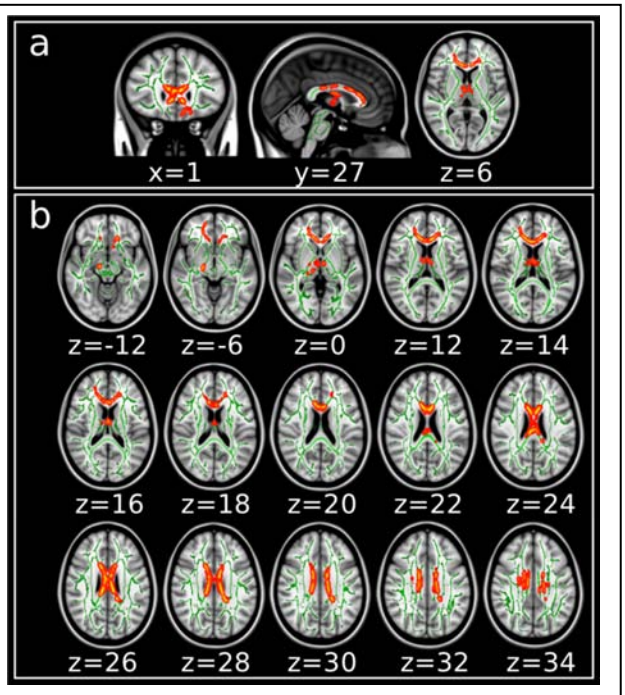

Figure 2. Results of the TBSS FA analysis for the mixed group. The MNI coordinates in a) and b) are the same as in Ref. [5] (Fig. 1 and Fig. 2) and are given below of each image. The regions detected with significant difference ($p < 0.005$) in FA of Tourette patients using the *tbss_fill* utility are shown in red. The green colour is used for mean skeleton.

Discussion and Conclusion: We addressed potential problems that frequently arise in clinical DTI studies due to the presence of artefacts. Corrupted dataset can be restored using this framework and returned into the clinical studies. The developed approach exhibits improved results compared to other methods as demonstrated in Fig. 1. The TBSS analysis with recovered datasets exhibits a high reproducibility of the results compared to the previous studies (see Fig.2). As an example, our approach might be useful for an estimation of other diffusion metrics in the non-Gaussian models or high angular resolution experiments where interplay between SNR and data abundance precedes the problem.

References: [1] Chang et al., 2005; MRM 53:1088; Chang et al., MRM, 2012 **[2]** Zwiers, 2010; NeuroImage 53:565 **[3]** Maximov et al., 2011; JMR 213:136 **[4]** Maximov et al., NeuroImage (submitted) **[5]** Neuner et al., 2010; NeuroImage 51:1184 **[6]** Koay et al., 2006; JMR 182:115